Design and Operational Concepts of a High Coverage Point-to-Point Transit System

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ABSTRACT

This paper presents the conceptual design and preliminary feasibility simulation results for a flexible transit system for travel from any point to any point based on real-time personalized travel desires, which is now possible due to advances in communication and computing technologies. While it is demand-responsive, the concept is significantly different from older demand-responsive transit systems, which were often failures. The proposed system requires high coverage, referring to the availability of a large number of transit vehicles (often minibuses or vans) which could also operate in conjunction with private and paratransit systems. The design strictly eliminates more than one transfer for any passenger. The system could potentially provide a transit alternative that is much more competitive with personal auto travel than conventional transit systems, due to significantly lower waiting times. The passenger demand for such a system is uncertain, but preliminary simulations show that under a variety of acceptable demand levels, the system can operate with high cost-effectiveness. The focus of the paper is in describing the details of the concept and providing arguments in favor of the system, based on simulations. The system essentially attempts to solve a stochastic real-time passenger pick-up and delivery problem with large number of vehicles. A strict optimization formulation and solution for such a problem is computationally prohibitive in real-time. The design proposed in this paper is effectively geared towards a decomposed solution using detailed rules that achieve vehicle selection and route planning. If real-time update of probabilities is included then this scheme can be considered as a form of quasi-optimal stochastic control.
1. INTRODUCTION

This paper presents a new conceptual design and preliminary feasibility simulation results for a flexible transit system for travel from any point to any point based on real-time personalized travel desires, which is now possible due to advances in communication and computing technologies. We strongly believe that research on this area must first develop conceptual designs different from older schemes for demand-responsive transit which have often proved to be failures.

Our research direction relies on certain premises, the primary one being that the failure of earlier demand-responsive transit systems stemmed from low passenger demands caused by excessive waiting time for patrons, poor coverage of the networks by demand-responsive vehicles, and poor computational algorithms and routing capabilities. Lack of flexibility for demand-side management was an added difficulty.

The proposed system is of “High-coverage,” referring to the availability of a large number of transit vehicles (often minibuses or vans – actually they could also operate in conjunction with private transit and paratransit systems) in a way where the travel option is at least somewhat competitive with personal auto travel. The design strictly eliminates more than one transfer for any passenger and introduces “passenger pooling” at pickup points with pooled passengers being able to travel to any destination thus avoiding a drawback of the “car-pooling” paradigm in auto travel. The cost-effectiveness of such a system directly depends on the passenger occupancy of the vehicles, and simulations will determine what level of supply in terms of transit vehicles, and what design of routing/re-routing schemes and transfer hub locations would render the system effective in a candidate urban context. In this paper, we outline the proposed concept, and provide results from initial simulations (which do not use some of the advanced routing schemes possible in the future) to show that the concept can yield a transit system that is efficient.

The new system relies heavily on new technologies for implementation, primarily information systems and vehicle location identification systems such as GPS and map displays. Real-time operations using automatic updating of vehicle routing in real-time, and information dissemination to the passengers in the vehicle as well as at home, is a key component. On a cursory look, the proposed system may look similar to paratransit systems (or taxis), but it has substantially different characteristics in terms of vehicle deployment, coverage design and application of technology. It is also a system ideally suited for much more efficient public investment than in conventional transit. It is perhaps deployable only by initial public investment, though it has tremendous flexibility in terms of potential private-public cooperation. A newly initiated research project (funded by the PATH program of the California Department of Transportation) is expected to yield implementable system design, routing guidelines and software, as well as lead to a field test with deployed advanced technology in the future. It is a public transit approach that will potentially remove the common criticisms about conventional transit systems and provide alternatives with much more competitiveness to personal auto, however an initial assessment of feasibility is needed, and that is attempted in this paper.

In section 4 we describe a simulation tool developed over an abstract network to analyze the feasibility of the system. Next, in section 5 we generate a study-case under several assumptions and first generation algorithms for solving vehicle routing issues. Finally, general conclusions and future research are emphasized in section 6.

2. BACKGROUND

The background research of significance to the new concepts in this paper mostly deal with demand-responsive transit systems.

Although demand responsive transit systems (henceforth DRT) have been in existence in several cities around the US, serious research into larger-scale demand-responsive transit did not start till the 1960s. Many demonstration projects (Peoria, IL, 1964; Flint, MI, 1968; Mansfield, OH, 1979) were only
marginally successful at best. The most intensive academic research into demand-responsive transit ("Dial-a-ride") was at MIT starting in 1970, in the well-known project CARS directed by Prof. Nigel Wilson. The work resulted in heuristic algorithms and a demonstration project by MIT at Rochester (1) and another demonstration project by MITRE Corporation at Huddersfield, N1. The generally accepted conclusion was that, perhaps due to the modest computational capabilities available then, manual dispatching performed better than computer dispatching (2). Although a lot of research has been spurred over the last years in this kind of problems, neither a successful methodology nor transit simulation results have been provided for solving large-scale demand-responsive transit systems.

A detailed description of the Paratransit services implemented in US is nicely presented by (3). Some innovative research in terms of automation of dial-a-ride systems, has been carried out by (4) over the last years (the well-known ADART system). He proposes a modern approach to many-to-few dial-a-ride transit operations, based on the most recent off-the-shelf consumer and computer technology. In addition, (5) and (6) describe the evolution of DRT systems, emphasizing some major issues to modernize dial-a-ride operations.

In terms of system design, work by (7) was the first foray in exploring a zone-based approach for dial-a-ride service. (8) extended this approach, adding line-haul connecting sub-regions and transfer points to the analysis. All these aspects along with the idea of combining fixed route and dial-a-ride services were initially considered in the Ann Arbor transportation system (9).

In terms of development of algorithms, two very exhaustive reviews and discussions of the various approaches proposed for solving dial-a-ride problems, are found in (10) and (11). They divide the pickup and delivery problems into static and dynamic cases, with single and multi-vehicle and, with and without time windows. Probably the most recent and important contributions in terms of routing algorithms have been developed by (12), (13), (14), (15), (16) and (17). However, due to the complexity of such algorithms, only small problems with 10 or 15 requests at most can be handled. In addition, (18) presents a preliminary study of the feasibility of checkpoint dial-a-ride systems, compared to a fixed route system with no transfers and door-to-door dial-a-ride systems. Analytical results show the situations in which a system is more attractive than the others in terms of cost-effectiveness. In fact, under simplified conditions, he analytically shows that as the demand level decreases, demand responsive systems become relatively more attractive than fixed route systems, and checkpoint systems might possibly become cost-effective.

A recent research summarized in (19) and (20) describes a new flexible collective transportation system. Their system considers conventional fixed route lines combined with lines based on flexible itinerary and timetable. The system exploits the idea that the integration of flexible "many to few" and "few to many" flexible systems, yields a "many to many" transportation system which is able to meet the personal transportation needs of a large customer set.

On the other hand, POCCS system developed first in Europe (21) is somewhat related to our research mainly because of technology aspects. Their objective was to integrate railway, bus, taxi, bus, school charter services and demand-scheduled means of transport into one uniform public transport network.

The primary problem faced by existing implementations of dial-a-ride systems is the low occupations found in the buses/avs and the resulting cost of operation. (2) reports some operating statistics for 20 of the larger demand-responsive systems in US for fiscal years ending in 1992. Vehicle productivity (average number of passengers picked up every vehicle hour) ranged from 1.44 to 5.31, with an average of 2.92. The resulting operating cost per passenger ranged from $6.23 to $18.34, with an average of $9.88. (2) also mentions another performance indicator, the level-of-service index, which is the ratio of request-to-arrival time by dial-a-ride to door-to-door travel time by automobile. The lower the ratio, the better the service. Experience shows that the index is usually in the range of 2.0 to 3.0 (i.e., 20 to 30 minutes waiting for a 10 minute trip). This means that demand-responsive systems tried in the past are absolutely not competitive with auto travel and thus will have low ridership, with normally only those without an available auto-option using it. The average passenger loads reported by (2) are very low, showing the inefficiency. A few numbers are even less than one, meaning that a large portion of the time
the vehicles are empty. That’s in part why efforts have been devoted to solving small problems, mostly oriented to the service of small communities or passengers with specific requirements (elderly, disabled).

The point is clear that if demand responsive transit is to ever become cost-effective, the occupancies in the vehicles should go up, at least to 3 or 6 passengers on average for van-type service, and 5-20 passengers for bus-type service. This will not happen unless the levels of supply of vehicles is significantly higher, and the time between call and service is significantly lower to make even those who think of transit as an option to select it over personal automobiles. If vehicles need to arrive fast enough after the call, what we can see is that one needs to be available within say 2 or 3 miles, which can be routed in such a way that the passengers can at least reach a transfer node for further travel. The waiting time at pick-up should be no more than 10 to 20 minutes. The design should also ensure that no more than one transfer is made by those traveling up to 10 or 15 miles, since this is an aspect that significantly affects the demand, and sometimes overlooked in transit network design.

We describe our proposed scheme next. The scheme proposed next combines many-to-one and one-to-many operation systems, considering both a trunk and a surface network, involving high level of supply (high coverage) and transfer hubs in demand-responsive transit.

3. HIGH COVERAGE POINT-TO-POINT TRANSIT (HCPTY): PROPOSED CONCEPT

The basic concept is based on one among a number of available transit vehicles (minibus buses or vans) being rerouted in real time, as a call comes in, with the transit vehicles being assigned to certain coverage areas ("cells"), say a hexagon of side k miles. The transit vehicles travel to transit "hubs", one of which could, for example, be designed for say seven of such "cells" (grouped as a "cell cluster" or "zone cluster"). Each transit vehicle has a "reroutable" portion of their trip in a cell it is assigned to and a non-reroutable portion on a trunk line to a given neighboring hub. With sufficient number of vehicles deployed in the system, one has the ability to travel to any of the adjacent hubs (up to, say, around, 20 miles away) and then transfer to another vehicle in a cell around that hub. The scheme is somewhat similar to the transit-center ideas for fixed route bus transit (22), except that the vehicles are routed within the cells around a hub in a demand responsive manner, and that vehicles would be available for travel with just one transfer (an important demand-side consideration) to points up to 10 or 20 miles away.

See FIGURE 1 for a candidate scheme. Note that in a real network, the cells could have any shape, but the hexagonal closed-pack cell structure shown here is convenient for illustration. The small hexagons are called "cells" here and the 7 hexagons around a transit hub form a "hub-region". For a passenger going from point A to point B, there may be different alternatives available, if there are sufficient number of vehicles deployed in the network. For cell of size 1.5 mile (9 ft.5), the distance between the hubs is roughly 7 miles, depending on whether there are grid-streets or whether there are freeways between the hubs.

< Insert FIGURE 1 here >

Traveler who wants to go from A to B can select a vehicle going from A to hub-2, where the vehicle is "reroutable" till hub-1, and then transfer to another line which is returning from hub-4, with a reroutable portion beyond hub-4. The same trip can be done taken a line from A to hub-4, transferring at hub-4, and then selecting a vehicle coming from any hub with "reroutable" portion after hub-4.

A preliminary evaluation of the efficacy of such a system requires careful simulation of passenger demand, to find out what the required occupancy (perhaps at least about 3 passengers per vehicle) can be achieved if service is provided with such vehicle coverage, for travel with one or preferably no transfers to any point within 10 to 20 mile radius of the passenger’s location. Note that in the FIGURE travel between two non-adjacent hub zones such as 2 and 3 may require more than one transfer; thus the system guarantees one transfer only for a chosen maximum distance. The detail of our proposed simulation experiment is explained in section 5.
The above description is only to give a rough idea of the system. There are several details of the scheme that can be evaluated only in realistic simulations. The locations of the transit hubs, the number of vehicles required per square mile area, etc., are important variables to focus simulations on. The questions include, whether all vehicles are required to have a hub-to-hub portion of the trip, whether the level of service significantly improves under different routing schemes and heuristics, which aspects of the design are the ridership most sensitive to, etc. The future work is expected to develop significant guidelines on the applicability of the scheme.

Next, we summarize the main aspects of our scheme:

- Smaller vehicles (7-seat vans or even cars, though regular buses also can be used) resulting in considerable savings in equipment purchase (several vehicles for the cost of a single bus). Driver salaries would offset some cost savings, however our studies so far have only looked at a very conservative 1 passenger/mile, which costs much less that what is spent on bus purchases in existing large urban bus transit systems.

- Lower fares (less than 1/3rd of taxi, average as low as $2 per trip) due to higher average vehicle occupancies - from 3 to 5 due to high coverage as opposed to 1 to 1.5 for DRT systems studied in the past. This also makes it different than taxi systems, which cannot achieve such occupancies.

- Vehicle occupancy can be improved with "passenger-pooling" or "stop-pooling" where passengers join at the same pick up spot, using ride incentives. Due to lack of restrictions in destinations, this would work much better than car-pooling using personal autos.

- Use of information technology, where Internet can be used by those at home to monitor how soon the vehicle will arrive. Use of GPS or other vehicle location systems for vehicle-monitoring and information update.

- Real-time demand generation and rerouting using information technology (even Internet).

- Recurrent demand from signed-up customers, as well as stochastic demand from others are handled.

- Various operational schemes such as real-time reassignment of vehicles to various other "some clusters" are possible if demand patterns vary in real time.

- "reroutable" and "non-reroutable" portions in the vehicle trips, with caps on number of reroutings.

- Implementation can be phased in and portions can be contracted out for private fleet operators.

- No more than 1 transfer, according to the proposed designs.

Such a proposed system is studied using a discrete event simulation approach in this paper. In what follows, we will describe the simulation procedure, detailing the objects, system states and events occurring throughout a simulation run. In section 4 we describe a particular implementation of the simulation concept, presenting some preliminary results analyzed in section 5.

4. SIMULATION: SCHEME AND COMPUTATIONAL IMPLEMENTATION

In the present section we describe the simulation framework developed for the preliminary examination of feasibility of the proposed system.

We coded a simulation in C++, based on a discrete-event system simulation approach (23). Roughly, discrete-event system simulation is the modeling of systems in which the state variable changes only at a discrete set of points in time. The change of state variables is determined throughout the execution of events. The events are scheduled and kept in a list (future event list) sorted by future occurrence time. When the next event (called the imminent event) is going to happen, the state of the components of the system is updated according to the imminent event features. The system statistics are updated and the imminent event is deleted from the future event list. The future event list changes dynamically as the events are either added to or deleted from it.

The C++ code is based upon an object oriented programming design, in which the vehicle is the central object of the system. In addition, we define two different kinds of events to happen: a transit vehicle state change and a customer call generation. The former defines the current state of a specific transit vehicle in the system at time t. The latter describes the generation of a new customer, specifying
his/her origin and destination coordinates. The occurrence of a vehicle state event schedules the next vehicle state (which is added to the future event list as a new event), unlike the call generation event which does not generate a next event to be added to the future event list.

In relation to the transit vehicle state event, the cyclic sequence of states (tasks) used in the simulation is as follows:

- **State 1**: Waiting to pick up a customer.
- **State 2**: Already assigned to pick up a specific passenger and going to his/her origin location
- **State 3**: Going from last origin of a call location to trunk network entrance point (can be origin hub or another point)
- **State 4**: Dropping passengers at origin hub
- **State 5**: Going from trunk network entrance point to final hub
- **State 6**: Dropping passengers at final hub
- **State 7**: Picking up passengers at final hub
- **State 8**: Going from intermediate hub to either first customer to be delivered if vehicle is full or origin hub otherwise
- **State 9**: Picking up passengers at initial hub
- **State 10**: TSP delivering of passengers

Note that this sequence of vehicle tasks simulates in a very simple way the proposed system presented in section 3.

In States 1 and 2, transit vehicle $j$ (of current position $H_j$) is available to pick up passengers over its assigned origin cluster zone, till it is full or till there are no more calls to pick up within the zone. The vehicle (among the available ones) fulfilling the minimum cost resulting from the call insertion in its current schedule should be the one that gets rerouted during the pick-up portion. In the experiments presented in section 5, we consider a simple cost function as a vehicle assignment indicator.

In State 3, if either the transit vehicle is full or there are no current calls generated, it proceeds to the trunk network and towards its assigned destination hub. We assumed a uniform distributed demand over the space, and therefore we assign our fleet homogeneously over the possible destination zones from each origin zone. Let us define $HB^{r}_j$ and $HB^{u}_j$ as the origin and destination hub zone of transit vehicle $j$ respectively. The vehicle could enter the trunk network either at the origin hub $HB^{r}_j$ or at any point along the route (we will choose the point minimizing the total travel time between the decision point and the hub destination as is shown in FIGURE 2). If the vehicle stop at the origin hub, it normally means that some passenger’s destination is different from that of the vehicle’s, and that they must be dropped there (State 4).

Our definition of pick-up vehicle availability, as mentioned above, considers vehicles assigned to the customer area in states 1 and 3, i.e., vehicles in their “reroutable” portion not currently assigned to pick-up a new customer.

Next, the vehicles travels along the trunk route till the destination hub $HB^{r}_j$ (“non-reroutable” portion of the route). At the destination, all the passengers must get off from the vehicle. Every passenger waiting at the hub with destination at the assigned vehicle zone (hub $HB^{r}_j$) should board the vehicle till the travel vehicle is full. Next, the vehicle goes back to its origin for picking up passengers waiting there to be dropped to their destinations within the corresponding cluster zone $HB^{u}_j$, (“reroutable” portion of the vehicle route). This involves States 5, 6, 7, 8 and 9.

Finally, an approximated algorithm is used for a TSP traveling salesman problem—solution in order to deliver passengers to their destination within zone $HB^{r}_j$. This algorithm operates in a very efficient way, and because the number of destinations to be visited by every vehicle is no more than about four to seven
points, the solution should match with the real solution of the TSP problem. After finishing the TSP tour, the vehicle is available to pick up new customers (State 1).

Note the simplicity of the demand-responsive routing algorithms for solving States 1 and 2. Although it is not clear intuitively how efficient such an operational design is, the simplified simulation could give us an idea about the feasibility of the system and the advantages of developing and implementing more sophisticated algorithms to support dynamic fleet management.

For example, note that State 4 and State 1 are solved sequentially, though solving the picking up and drop-off processes simultaneously would be more efficient. Taking advantage of the lower vehicle load along the TSP route, especially when the vehicle is delivering the last passengers of the sequence. Such operational schemes are currently being developed and implemented into the system.

In addition, from the simulation results showed in section 5, we realized that the computer time required to running the routing algorithms is not an issue even considering a high demand levels and big fleet sizes. This means that we may have already solved a serious concern in earlier field studies of DRT, where routing over larger networks caused TSP problem solutions to cause computational delays. The distributed nature of our approach appears to be what gives us benefits on the routing side. However, there are even better routing schemes that could be developed for further efficiency and optimality, especially when real-time operations with overlapping operational zones are considered. In the next section, we present our preliminary simulation experiments, emphasizing all the assumptions and some interesting results obtained from them.

In FIGURE 2 we show graphically the vehicle schedule described in this section.

5. SIMULATION ASSUMPTIONS AND ANALYSIS OF RESULTS

5.1 Generalities

In this paper, the simulations conducted are strictly to show initial feasibility. Thus certain simplifying assumptions have been made. Schema's for routing vehicles using real-time updates of probabilities and elaborate expected cost values, described later, are not used in the simulation since they require application to a real network with real-time dynamic traffic and demand conditions.

The experiment was carried out over a simplified network considering different levels of service. These simulations do not run a real network. The simulations themselves are based on approximate travel-time calculations, to show initial feasibility. Also, the smaller cell sizes would reduce the travel times while keeping the waiting time at pick-up somewhat attractive, as we use essentially the same fleet size density (1 or 2 per square mile, as in the concept section). Thus the initial study is performed to look at the worst case performance of the system. As the results indicate below, we were able to find competitive fleet usage results and wait-time travel-time results.

We simulate a demand-responsive transit system over an area of 165 square miles. This area is divided in four cluster zones, each containing a total of seven hexagonal cells inside each one side 1.5 miles. This results in approximately equal distance between adjacent hubs (centroïd of the cluster zone) of about 7 miles. Transit vehicles could initially be located at any cell zone centroïd, including of course the hub location itself, in order to take advantage of the terminal capacity already implemented there.

For the "non-recurrent" portion of the vehicle trips, the travel is assumed to be along a trunk network between hubs. Euclidean distances and a 50 mph speed are assumed for travel. On the other hand, for the "recurrent" portion of the vehicle routes (within cell zones) the level of service is assumed to be worse than that on the truck network. A combination of Manhattan and Euclidian travel distances and 25 mph speed are used.

The demand is generated randomly in the simulation, because at this point demand models for this kind of service are not available. We assume the call generation following a spatial uniform distribution over the study area. The call frequency is random, according to a Poisson process with mean
A (pax/hr-square mile). In this study $\lambda = 2, 3, 4, 5$ are considered. These are numbers comparable to existing transit demand in many U.S. cities, though the new system could potentially generate much higher demands; thus, these are conservative numbers. For now, we assume that our vehicles are vans (with capacity say 7 pax/vehicle).

The boarding times are assumed to follow a normal distribution $N(20, 1.0)$ per customer at pick-up location and a uniform distribution (say between 5 and 10 seconds per customer) at a hub. The alighting time is considered uniformly distributed between 0.5 and 1.0 minute per customer at the destination, and between 5 and 10 seconds per customer at a hub terminal.

The most conservative assumptions are related to the pick up decision (involving vehicles in States 1, 2 and 3) and delivery (State 10) procedures. First, we simulate the case in which the transit vehicle assigned to pick up a call already in the queue of customers waiting the one closest to the customer location at the moment of the decision, restricting this decision to vehicles in States 1 and 3. Second, vehicles in State 2 are not allowed to change their just assigned passengers dynamically by a new appearing customer, even though this operation could eventually make the whole system be better off. Third, vehicles in State 10 (dropping passengers) are not allowed to pick up a customer until delivering all the customers on the vehicles.

The approximate TSP algorithm tour coded for solving the passenger-drop problem is the well known nearest-neighbor algorithm (24) which turns out to be very effective for solving problems of this size. Its efficiency is measured in terms of computational time involved and optimality of the resulting TSP tour as well.

In addition, we attempt certain demand-control as well. This refers to the assumption that we will have a certain average number of passengers at each pick-up. We introduce certain probability of having more than one person waiting to be picked up at any origin (say $p=1/3$). Additionally, among all the waiting origins, we assume another probability of having one or two additional people waiting there (say 0.5 for each case). This is a relatively controllable demand pattern, as fare incentives can be used to encourage passengers to "pool" together at stops.

Finally, under the above assumptions, we run three hours of simulation. The most important point to be analyzed from the results of the simulation is the trade off between cost effectiveness of the demand-responsive system (directly depending on the average load of the vehicles) and the level of service offered (measured through passenger waiting and travel times).

5.2 Pick up decision: cost function analysis and proposed routing algorithms

The decision taken by either a manager or the vehicle driver in order to assign a specific customer to a specific transit vehicle is, doubtless, one of the most difficult decisions to be modeled and simulated properly. A large number of heuristic algorithms based on different approaches have been developed in the literature to deal with this problem. However, none of them has been designed to take efficient pickup decisions for a dynamic system like HCPP

Currently, we are developing algorithms and strategies to solve this assignment decision efficiently, including issues like dynamic update of stochastic control variables, new routing schemes and so on. So far, we have developed some simplified system cost function expressions along with some preliminary pick-up strategies. Note that our pick-up algorithms have been developed independently of the TSP algorithms implemented for delivering passengers. A combined strategy (simultaneous pick-up and delivery) shall be introduced in section 5.2.2.

First, we define the mathematical notation that we will use throughout the entire section. All the variables are defined for a specific time instant $t$. Henceforth, we will omit any index $t$ in order to simplify the notation.

General notation:

i) An arbitrary cluster zone $i$ is represented by $H_i$

ii) An arbitrary customer (or call) $z_j$, has the following characteristics:
• \(\text{origin}_i\_\text{call}_j\_\text{coordinates} = (x_{o_i}, y_{o_i}) = z_{i}^o\)
• \(\text{destination}_i\_\text{call}_j\_\text{coordinates} = (x_{d_i}, y_{d_i}) = z_{i}^d\)
• Hubs associated to \(z_i\):
  - \(\text{HH}_i^o = H_j\) for some \(p\)
  - \(\text{HH}_i^d = H_j\) for some \(q \neq p\)
• \(p_i\) number of customers waiting at \(z_i^o\) ("pool size")

iii) An arbitrary vehicle \(j\) has the following features:
• Position coordinates: \(B_j = (x_{b_j}, y_{b_j})\)
• \(L_{ij}\) load in vehicle \(j\) in (pax/vehicle)
• Vehicle capacity: \(L_{\text{max}}\) \(\left( L_{ij} \leq L_{\text{max}} \right)\)
• \(\text{HH}_i^o\) origin hub associated to \(B_j = H_s\) for some \(r\)
• \(\text{HH}_i^d\) destination hub associated to \(B_j = H_s\) for some \(s \neq r\)

iv) Additional performance measure:
• \(E_{\text{pick}}^{\text{dist}}(H_s)\) : Expected pickup time per pax at home (Hub \(H_s\))

v) Travel time expressions at any time \(t\):
• \(t_{ij}(a,b)\) : local network travel time between points \(a\) and \(b\)
• \(t_{ij}(a,b)\) : trunk network travel time between points \(a\) and \(b\)
where: \(t_{ij}(a,b) = D_{\text{local}}(a,b)\) and \(t_{ij}(a,b) = D_{\text{trunk}}(a,b)\)

\[D_{\text{local}}(a,b) = \delta \left[ \sqrt{ \left( x_a-x_b \right)^2 + \left( y_a-y_b \right)^2 } \right] + \left( 1 - \delta \right) \left[ \left| x_a-x_b \right| + \left| y_a-y_b \right| \right] \quad (1)\]

\[D_{\text{trunk}}(a,b) = \sqrt{ \left( x_a-x_b \right)^2 + \left( y_a-y_b \right)^2 } \quad (2)\]

where \(\delta\) is an arbitrary parameter (we use 0.5 in our experiments) and \(v_o\) and \(v_t\) represent the average speed on local and trunk networks respectively.

5.2.1 Simple heuristic rules

The pick-up rules developed here will be applied to vehicles in States 1, 2 and 3. Basically, when a call is generated, it enters to a queue of waiting customers within a specific hub zone. Among all the available vehicles in the zone, the one with minimum cost \(C_j\) is assigned to pick up customer \(z_i\). \(C_j\) is calculated as follows:

\[C_j = \left( L_{ij} + p_i \right) \frac{D_{\text{local}}(B_j, z_i)}{v_o} \quad (3)\]
The previous expression is a simple representation of the user cost function, in which the travel time spent in picking up $z_i$ is weighted by the number of people already on the vehicle plus one. This additional unit represents the extra waiting time of customer $z_i$ if assigned to vehicle $j$. Different weights for travel and waiting times could be incorporated in future experiments along with an operator cost component.

After some preliminary experiments, we realized that most of the transfers occurred at the origin hub (Vehicle State $I$), because vehicles picked up several passengers whose destination was different from that of the vehicle. This operation generates inefficiency since the vehicle cannot access the trunk network at the optimal point. In addition, waiting time at hub increases because customers have a smaller chance of taking the right vehicle. In order to solve this difficulty, we incorporate a penalty value $\theta$ defined as follows:

$$\theta = \begin{cases} \theta & \text{if } H_i \neq H_j' \\ 0 & \text{otherwise} \end{cases}$$

The penalty $\theta$ is measured in time units. Finally, a new expression for calculating $C_j$ is generated. Analytically:

$$C_j = \left( L_j + p_j \right) \frac{D_{\text{hub}}(B_j, z_j^*)}{v_0} + \theta$$

(4)

In addition, if we wanted to expand the available vehicle set, we should analyze vehicles in $State 2$ besides those in $States 1$ and $3$. In that case, we are changing dynamically a previous pick-up decision, and therefore we should consider not only the cost associated to the $L_j + p_j$ customers involved, but also the extra cost associated to the customer previously assigned to the route of vehicle $J, n_j$. Thus, if vehicle $j$ is in $State 2$, expression (4) turns to

$$C_j = \left( L_j + p_j \right) \frac{D_{\text{hub}}(B_j, z_j^*)}{v_0} + \frac{D_{\text{hub}}(B_j, z_j^*)}{v_0} + \frac{D_{\text{hub}}(B_j, n_j)}{v_0} + \frac{D_{\text{hub}}(B_j, n_j)}{v_0} + \frac{D_{\text{hub}}(z_j^*, n_j)}{v_0} + \frac{D_{\text{hub}}(z_j^*, n_j)}{v_0} + \frac{p_j \cdot E_{\text{hub}}(H_j')}{v_0} + \frac{p_j \cdot E_{\text{hub}}(H_j')}{v_0} + \theta$$

(5)

The second term in equation (5) represents the additional cost incurred in not picking up the customer $n_j$ by vehicle $j$. In the simulations, we used $\theta = 15$ minutes, which appeared to provide the best routings among several values tried in preliminary experiments.

5.2.2 Stochastic heuristic rules combining pick-up and delivery decisions: An overview

All pick-up rules described in expressions (4) and (5) are very straightforward and work reasonably well in terms of system performance and productivity levels, although there are too many factors not being considered here. It is easy to see that the system performance should improve considerably if we incorporate some more sophisticated rules to account for fundamental issues such as the dynamic nature of the system. Since calls are generated dynamically and the pick-up and delivery decisions are taken in real time based on system information at the decision time, decision rules are developed that depend on the expected number of future insertions into pre-established vehicle routes. Note that passenger assignments could change over time because of changes in system conditions. Thus, a new generation of algorithms is being, considering stochastic travel times to be expected for future assignments. These travel times can be calibrated online based on historical information regarding the performance of the
system, just as in closed loop feedback control systems. This capability of fine-tuning the system is what essentially brings out the optimal nature of the solutions. In this process, we essentially accomplish a notion of optimality in a problem that in a pure optimization formulation as a stochastic pick-up-and-delivery problem is computationally prohibitive (as the real examples will include 10s of vehicles and passenger calls (pick-up points) which are many-fold the routings is still based on optimal TSP calculations, but within r decomposed solution space thanks to the cell-structure of the design. However, real-time values updated for travel times and expected number of pick-ups, would yield results conceivably better than from solving approximated versions of classical pick-up-and-delivery problems. We must also mention that we have indeed generated classical optimization formulations which do not rely on such designed decompositions, but we cannot even consider providing comparative solutions, as we are unable to solve them due to the number of vehicles and demand points.

The new heuristics are based on the following criterion: when the dispatching program receives a new pick-up request, it evaluates the additional cost over the known system (including operators and passengers) resulting from the insertion of such a customer into the expected route of all candidate vehicles. Then, the requested service is assigned to that vehicle with the minimum incremental cost. The important issue here is to have correct expressions for such generalized costs. Such a pick-up decision could eventually impact the current status of the system at a hub area level, since the chosen vehicle could be a good candidate to serve other pending pick-up requests assigned to different vehicles at a lower cost. If so, these vehicles could potentially change their schedules and routes too, resulting in a series of vehicle route adjustments until no further improvements occur. We have developed such heuristics to reasonably adjust vehicle schedules and routes in order to deal with this dynamic local imbalance, without adding excessive complexity to the formulations. No simulation results using such a scheme is provided here, as they rely on on-line update of probabilities. Such updates can be done correctly only with simulations of real-world demand generation and bus movements in a real-network of high-way links, as opposed to a continuous space simulation we have done in this paper. Such simulation models are currently nearing completion.

Let us illustrate these new stochastic concepts with a simple example. Suppose that two vehicles (say, vehicles j and k) are available to pick-up new requests within certain hub region, and they currently have a pre-established sequence of stops, including scheduled pick-ups and deliveries as shown in FIGURE 3:

< Insert FIGURE 3 here >

Note that vehicle k has to access the trunk network at the hub position since the destination hub of its scheduled pick-up z_k is different from its own hub. At time t (when vehicles are in positions B_i and B_j) a new pick-up request z_j is introduced in the system. There are two options for the manager to schedule that request, whether into the route of vehicle j or into the route of vehicle k. Suppose that in both cases, the best option is to insert the new request immediately. That means, before delivering passenger d_j in case of vehicle j, and before picking-up group of passengers z_j waiting at their origin in case of vehicle k. A strict cost function formulation should incorporate all these effects when computing the additional cost incurred in making such an insertion. The two candidate insertions are shown in FIGURE 4.

< Insert FIGURE 4 here >

Note that after inserting z_j into vehicle j route, it has to stop at the origin hub before keeping going till its associated destination hub, since z_j customer is traveling towards a different destination.
Therefore, the manager must decide which insertion results in a lower cost to the system over the base situation in FIGURE 3. For this particular case, the decision will be based on

\[
\begin{align*}
\Delta C^i_j &= C^i_j(z_j) - C^i_j^{(0)} \\
\Delta C^i_k &= C^i_k(z_j) - C^i_k^{(0)}
\end{align*}
\]

(6)

where \( C^i_j(z_j) \) and \( C^i_k(z_j) \) represent the cost incurred by vehicle \( j \) on all its scheduled passengers (on board and waiting to be served) in case of inserting the new customer into its original route. \( C^i_j^{(0)} \) on the other hand, represents the cost on the system if vehicle \( j \) continues to follow its original schedule. For this particular case, expression (6) is calculated by summing the incremental cost between stops over the entire sequence. The manager will assign customer \( z_j \) to that vehicle with a lower \( \Delta C \). Suppose that \( \Delta C^j_i < \Delta C^k_i \). Thus, customer \( z_j \) will be inserted into vehicle \( j \)'s route. After taking that decision, the system needs to be adjusted since vehicle \( j \) could now eventually serve a customer already scheduled to another vehicle's route (say, route \( k \)), if that decision represented a potential improvement.

Besides, the cost criterion remains the same, with the difference that in this case we have to compute the incremental cost of adding one customer to one vehicle route, and compare that increment in cost with the decrease in cost due to excluding that customer from his original scheduled route. In our example, if customer \( z_j \) were assigned to vehicle \( j \), this vehicle could also pick-up customer \( z_j \) originally assigned to vehicle \( k \). In fact, if the incremental cost of inserting \( z_j \) to vehicle \( j \) route \( \Delta C^j_i \) is smaller than the benefit of excluding that customer from the \( k \) route \( \Delta C^k_i \), the manager could take the decision of adjusting both vehicle schedules. In FIGURE 5 we show graphically the possible impact of such a modification. The diagram on the left shows the original assignment while the one on the right shows the impact on the system after this adjustment.

< Insert FIGURE 5 here >

Given the dynamic nature of these decisions over time, we can realize that in order to take realistic pick-up decisions, we should accept that travel time variables in the cost formulations are stochastic, and they will depend on the expected number of insertions not scheduled when taking any pick-up decision. Let us illustrate this new concept with an example:

Before insertion, vehicle \( j \) had scheduled a sequence of stops \( \{d_1^j, d_2^j, d_3, HB\} \). If conditions had remained invariant over time, the travel time spent from the current location and the first delivery \( d_1^j \) would simply be the travel time between the two physical points, given the network traffic conditions at the time of that trip. If vehicle \( j \) were assigned to pick customer \( z_j \), the travel time between the same two points would increase considerably (1 intermediate stop), and if the adjustment situation in FIGURE 5 occurred, it would increase even more (2 intermediate stops). This uncertainty in travel time due to extra stochastic insertions over time is directly related to the cost expressions, which depend explicitly on travel time, and therefore, is strongly related to the decision rules.

< Insert FIGURE 6 here >

FIGURE 6 shows the possible values that the travel time between the vehicle \( j \)'s current position and its first delivery, based only on the possible situations described above. The possible combinations can become increasingly complicated, depending on the demand, the number of vehicles available, and so
on. We are currently developing the stochastic formulation in order to incorporate expected travel time estimates into the cost function expressions. For the simple case in Figure 6, since we don't know with certainty the future vehicle assignments, we could assume that there is a probability \( P_j \) that vehicle \( j \) completes its first delivery assignment without any reschedule (diagram A). If, on the other hand, vehicle \( j \) is deviated to pick-up \( z_j \) (diagram B) with probability \( (1 - P_j) \), there is also a probability that from there, vehicle \( j \) could pick-up an extra passenger \( z_2 \), with probability \( (1 - P_j) \), diagram C. Thus, under this simple condition, if \( t^d_j(B_j, d_j') \) is the base travel time between the vehicle position and its first delivery, the expected travel time in arriving to its first delivery will be

\[
E_t[B_j, d_j'] = P_j t^d_j(B_j, d_j') + (1 - P_j) t^d_j(B_j, z_j) + (1 - P_j) t^d_j(z_j, z_2) + t_j(z_2, d_j') + P_j t^d_j(z_j, d_j')
\]

(7)

The real expressions under more realistic conditions become much more complicated. These probabilities can be updated in real time using information obtained from the system itself. The final expressions and applications will be reported in a future work.

5.3 Case study results

We adopt the system performance measures discussed by Alan Black in (2) in order to analyze the system design efficiency and performance under different simulation conditions and different demand levels as well. We first define the level-of-service index at hub level \( \phi_j \) as follows

\[
\phi_j = \frac{\text{Average passenger waiting time at pick-up location}}{\text{Average door-to-door ride time}}
\]

(8)

where the denominator ride time is calculated as the average door-to-door ride time from hub \( j \) to all the adjacent hub destinations. We also introduce another performance index, the ride time index \( \rho \) defined at system level. That is

\[
\rho = \frac{\text{Average vehicle ride time}}{\text{Average door-to-door ride time}}
\]

(9)

The door-to-door ride time is the time of travel when no other passenger is picked up. We obtained an average door-to-door ride time (average weighted by the number of instances per origin-destination pair) equals to 31.76 minutes, in a separate calculation

Elaborate research is needed to find "optimal" operational schemes. The intent in this paper is only to show a reasonable operational scheme and to show that even such a system can show good performance. We however attempt to find routing procedures that yield reduced ride and waiting times.

It is beneficial to balance the vehicles' spatial distribution among the different portions of the trip at any time. Specifically, we think excessive ride times are due to the inefficient assignment of vehicle in Stages 1, 2 and 3 when the number of available vehicles to pick-up a passenger is too low. So, if the number of available vehicles is less than 1/3 of the total vehicles assigned to a cluster zone (say 14 vehicles), we decide not to assign a vehicle unless the cost involved in picking up the customer wanting for service is less than an arbitrary value \( C_{MAX} \). We test four values for \( C_{MAX} \) in time units: 10, 15, 20 minutes and of course \( C_{MAX} = \infty \), which means, no cost restriction.
Final results are reported in TABLE 1 and FIGURE 7 next. Note that in FIGURE 7 we use $C_{\text{MAX}} = 50$ for the unrestricted case (i.e., $C_{\text{MAX}} = \infty$), only for simplicity of the graphic representation.

TABLE 1 shows the performance statistics for different routing patterns (resulting from various $C_{\text{MAX}}$ values). Ride times are found to be as low as 34.43 minutes, resulting in a ride time index of 1.08. This index shows the rate between door-to-door service ride time and the resulting ride time provided by our system. So, $\rho = 2.08$ means that the ride time provided is a 8% more than that provided by a competitive door-to-door service. For example, under the lowest demand level reported in TABLE 1, for a 10 minutes door-to-door trip, our service could offer the same service in about 11 minutes. On the other hand, for higher demand levels, $\rho$ does not exceed 1.58, which is in any case, better than the values reported in previous DRT experiments.

Waiting times up to 10 or 20 minutes at pick-up (for lower demand rates), and around 30 minutes for higher demand levels, are very reasonable for this system. It is comparable to taxi services, and is better than in the dial-a-ride services of the past and possibly no worse than the walk and wait time in fixed route transit services as well. In addition, waiting time can be rescheduled to other activities if the pick-up is at home. $\theta$ (level of service index) values represent the importance of the waiting time at home compared with the ride time itself. Previous DRT systems have shown values up to even 2 or 3 (i.e., waiting times were two to three times travel times) were unacceptable, however we found values as low as 0.26 and no greater than 1.05 in the worst case. $\theta = 0.26$ means that for a 20 minute trip, the user must wait around 5 minutes until service. Also waiting times at hubs are low enough (no more than 11 minutes in the worse case). However, there is a tradeoff between these two indices, reflected through the adopted routing strategy. FIGURE 7 shows in detail the tradeoffs between the two indices for different routing patterns (resulting from various $C_{\text{MAX}}$ values). Note the opposite tendency between indices. Also, we can appreciate that vehicle productivity increases with $\rho$ and decreases with $\theta$, as expected. In other words, if we decide to impose a strategy in order to improve ride times (lowering the ride time index), it could result in worse productivity levels.

With regard to the productivity measure, average load (in passengers/vehicle), the results could be better, but for the load difference between the “renrouteable” and the “non-renrouteable” portions (3.81 and 0.69 in the most extreme case). For details, see TABLE 2 with disaggregated information for a demand level of 5 pax/sq. mile, and $C_{\text{MAX}} = 20$ minutes. Note that there is a considerable imbalance between the loads in the “renrouteable” and “non-renrouteable” portions of the system.

For the particular case reported in TABLE 2, we can see that on a Pentium III the routing takes virtually no time at all, mostly due to the few delivery points and with picking up being handled using heuristics, which is easy under high coverage. Also the small vehicle sizes cause not more than 5 or 6 delivery points, thus an approximate TSP can be used. Note that computation time was just 0.0108 seconds per TSP function call. Computation time for routing was considered a problem in the past DRT system but this is not a concern in the newly proposed system.

6. CONCLUSIONS AND FUTURE WORK

The main goal of this paper was to present a new design concept for implementable demand-responsive transit systems, which rely on real-time communication and computing technologies, and advanced routing algorithms for efficient operation. We have developed the system design and simulated an abstract system under certain conditions and simplified routing algorithms so far. In spite of that, results
show considerable improvements respect to previous DRT system implementations, specially considering the level-of-service and ride-time indices, between 0.31 to 1.00 and 1.18 to 1.38 respectively, compared for example with levels of services between 2.00 to 3.00 reported in the past. However, it may be noted that the new system is not directly comparable to older DRT systems and that the results could be different depending on the network and demand contexts. Furthermore, the need for more depots, etc., would need to be studied in elaborate detail before cost comparisons can be made.

On the other hand, the vehicle productivity reflected by average passenger load is still low, but reasonable even for the simulated cases, considered a worst-case than the better designs proposed in the concepts section. Average passenger loads between 2 and 3 makes it much better than the 1 to 1.5 reported for earlier demand-responsive systems. This number can be improved substantially by using information technology, and also by implementing algorithms based on probabilistic system conditions in order to anticipate demand patterns avoiding worthless portions of the vehicle trips, in which they travel practically empty. Coordination between hub locations and use of information on waiting passengers, etc, can be used for much more efficient routing schemes than attempted here. The fact that the results are still very good, shows the promise the new concept has.

Average waiting times are very reasonable especially at hub terminals. Additionally, the order of magnitude of 10 to 20 minutes of waiting time at home is very good considering the location of this activity (the customer can do a different activity at home while he waits the vehicle). Additionally, the average waiting times at hub are also reasonable. The ride times good enough if we take into account the high demand level simulated considering a personalized transit system like this. At this point, we should emphasize that this is our first feasibility experiment, with several strong assumptions and simple algorithms to be improved in future simulations.

Finally, we can mention an important point, taking into account that in both cases the computational efforts (in calling the routing algorithms used) are not an issue anymore. Twenty years ago, because of the modest computer capabilities available then, researchers realized that manual dispatching performed better than computer dispatching. Now, we can estimate insignificant computer times running the algorithms, allowing managers to take routing decisions almost in real-time. We realize that we must code more complicated and sophisticated algorithms to improve level of service and productivity, however we at least can mention some first order of magnitude consistent with our purposes. The pilot study certainly indicates that the schemes have a reasonable chance to be successful if proper fleet operations schemes are developed. This gives validity to our concepts, and detailed simulations in the future will give much more conclusive evidence if such a system is worth field testing.

Acknowledgement

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(Each \( C_{\text{sat}} \) shows a different routing pattern)
<table>
<thead>
<tr>
<th>Demand (pax/sq. mile-hr)</th>
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<th></th>
<th></th>
<th>3</th>
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<td>15</td>
<td>20</td>
<td></td>
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<td>1.55</td>
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<td>46.33</td>
<td>42.76</td>
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</table>

| 3  | return | nr | 8.34  | 0.69 | Average load | 2.83  | (pax/veh) |
| r  | 15.94 | 2.93 | Percentage of free vehicles | 0.000 |
| total | 64.41 | 2.61 | Level of service matrix | 1 | 2 | 3 | 4 |
| on/going | r | 28.62 | 2.54 | Level of service matrix | 123 |
|     | nr | 8.79  | 3.11 | Level of service matrix | 107 |
| 4  | return | nr | 8.53  | 1.84 | Demand (pax/UT) | 143 |
| r  | 31.99 | 3.37 | Level of service matrix | 1 | 2 | 3 | 4 |
| total | 78.12 | 2.87 | Level of service matrix | 3 | 143 |

**Traveling salesman problem approximated Algorithm**

| Function call | 252 | (times) | 1 | 2 | 3 | 4 |
| Total resource time | 2.73 | (sec) | 1 | 4.78 | 4.78 |
| Average resource time function | 0.0108 | (sec) |
| Average number of pax dropped | 5.643 | (pax/TSP) | 3 | 0.73 | 0.73 | 0.73 | 0.73 |
| One pax delivery | 21 | (times) | 1 | 2 | 3 | 4 |

* r: reroutable portion of the trip
* nr: non-reroutable portion of the trip